Accelerated Scientific Discovery with AI-driven Experiments in support of IFE

IFE Workshop

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Acknowledgements

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This community has already identified many of the applications of ML/AI for IFE research

Scott, G.G.	Lawrence Livermore National Laboratory	High repetition rate diagnostics with integrated machine learning analysis for a new paradigm of actively controlled Inertial Fusion Energy experiments
Heuer, Peter	Laboratory for Laser Energetics, University of Rochester	Accelerating the science, technology, and workforce base for inertial fusion energy with a proposed high repetition rate facility
Gopalaswamy, V.	Lawrence Livermore National Laboratory	Validating IFE Concepts with Machine Learning Driven Design Optimization

Summary

Integrating Machine Learning and Artificial Intelligence will be key to full utilization of HRR for accelerated scientific discovery

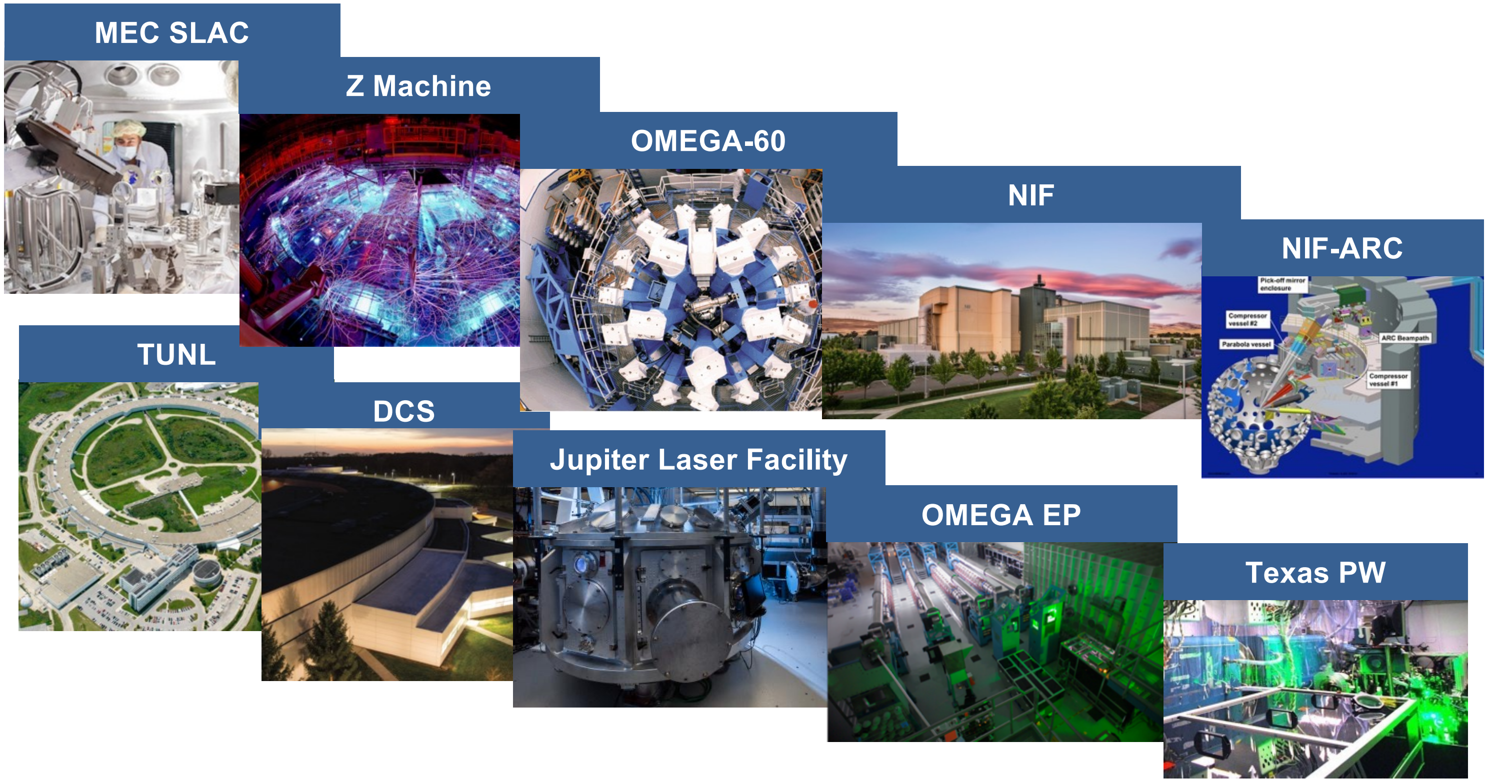
Key Metrics

- Laser technology has enabled high-energy (10's J-kJ) multi-Hz operation → data throughput by ~36,000X.
- Control systems still require "hands on" operation. Need ML for fine control/stability for IFE power plant.
- "Big Data" (TB/s?) handling through AI will be necessary to filter, analyze, and retain important data.
- ML analyzed diagnostic data → μs-ms timescales (>1,000X speed)
- Surrogate models from ensemble simulations to scan multi-dimensional parameter space. >1,000X faster
- Comparison/retraining during HRR experimental operations → optimization and exploration

The revolution in computational power and machine learning techniques paves the way for new approaches in data analysis, prediction, and comparing simulation and experiment

Motivation

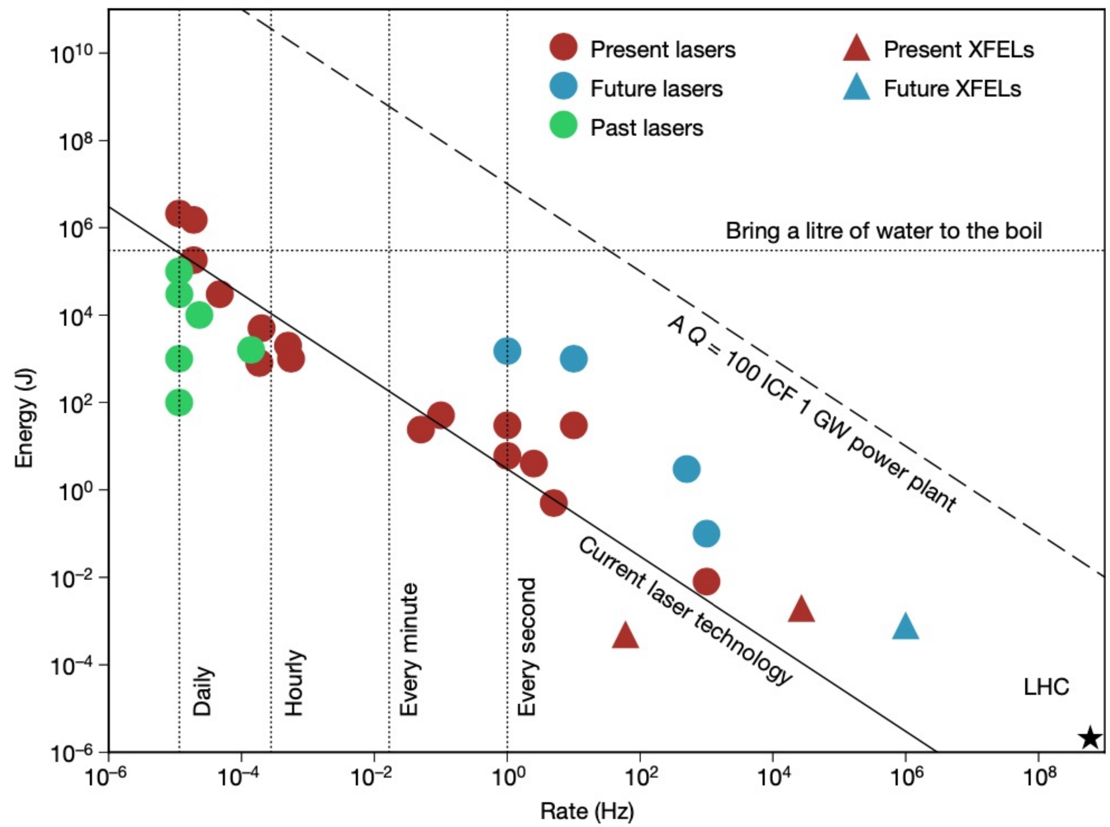
Currently we make use of a number of premier facilities around the US & the world to conduct forefront HED science



HED science has focused on large, energetic drivers that are mostly single-shot (>shot/30 min)

Current/Future Lasers

In the near-term, laser drivers are moving toward higher repetition rates



P. Hatfield, et al., "The data-driven future of high-energy-density physics", Nat. Persp. (2021)

Current/Future Lasers

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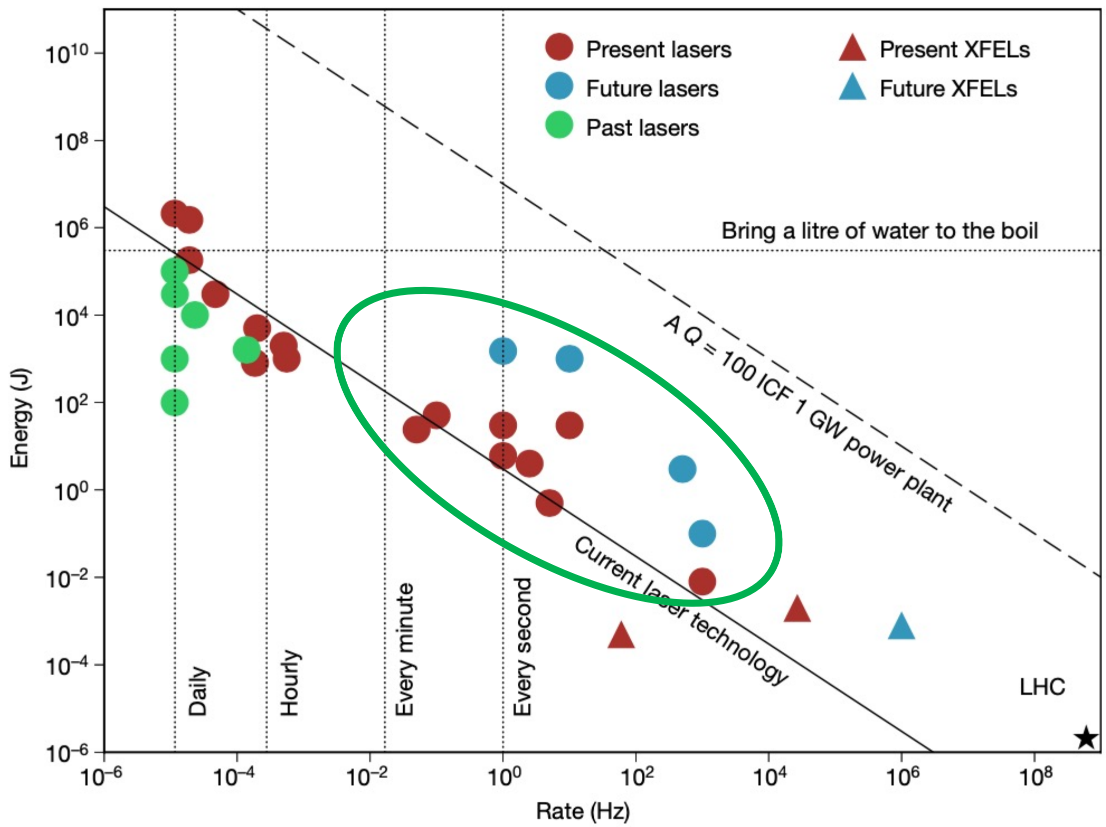
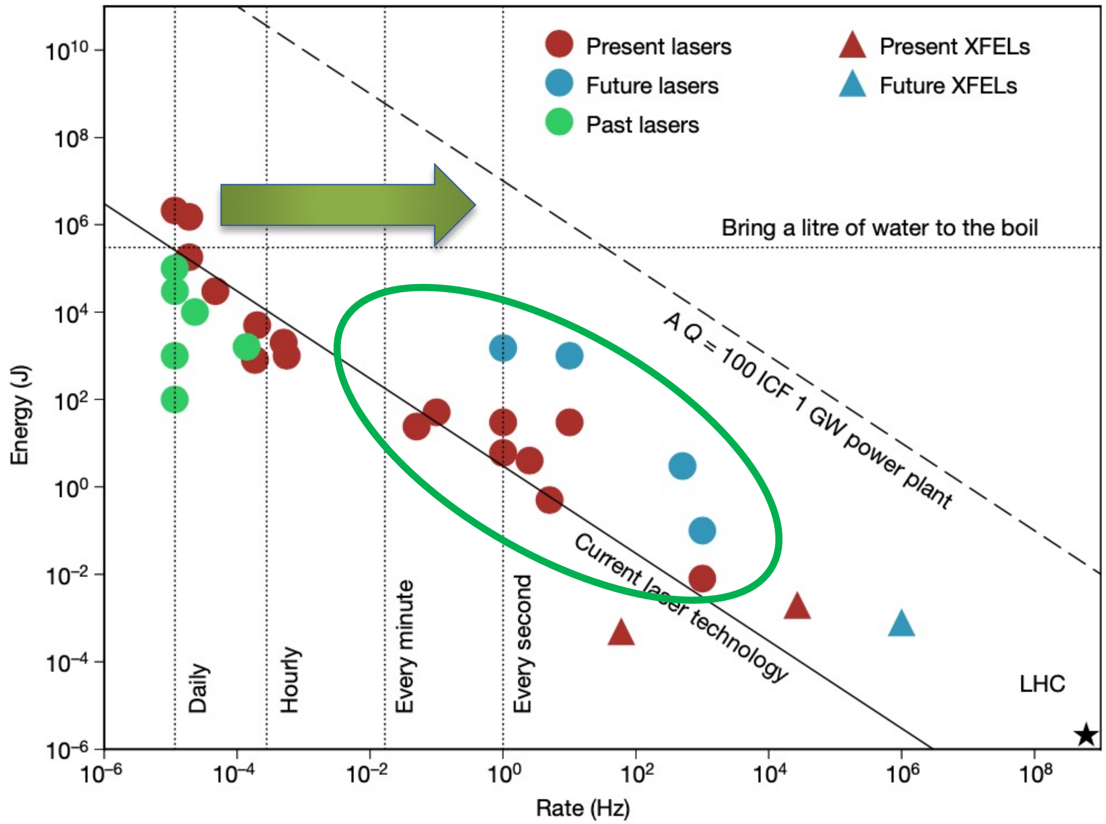


P. Hatfield, et al., "The data-driven future of high-energy-density physics", Nat. Persp. (2021)

Current/Future Lasers

Gaps in rep-rate and energy (scale) will need to be bridged for IFE, but there are still many challenges to enabling true HRR experiments

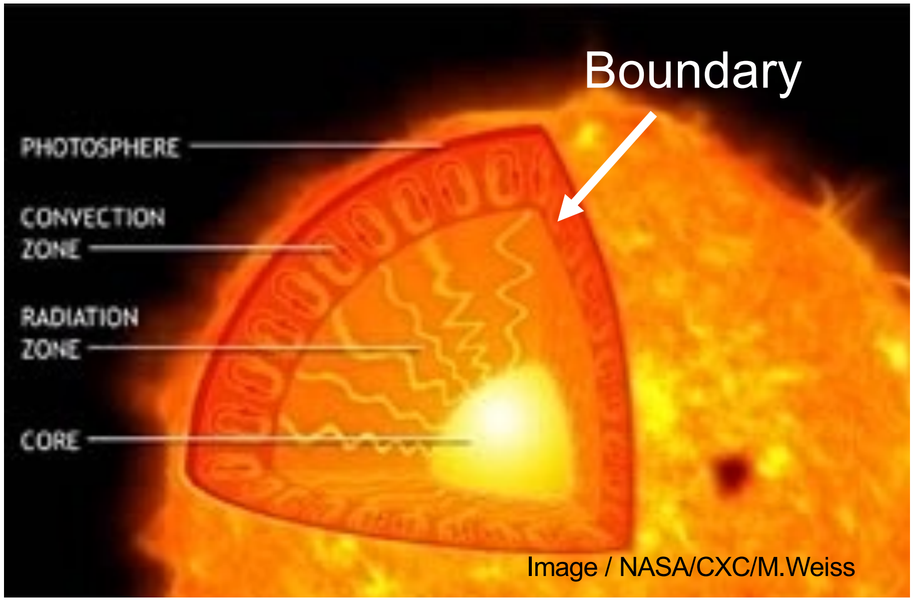


P. Hatfield, et al., "The data-driven future of high-energy-density physics", Nat. Persp. (2021)

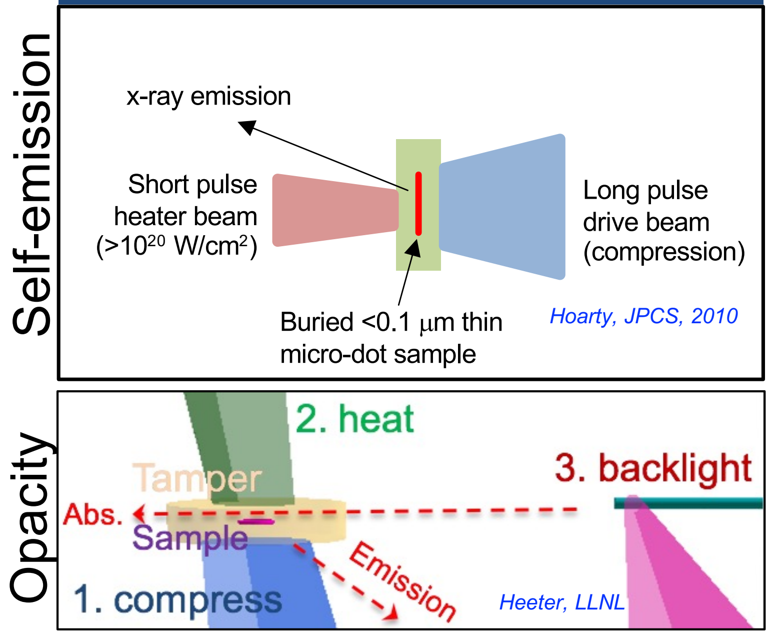
Examples: Science

HRR will provide the 10,000's of shots to adequately provide opacity and radiative properties benchmark data

Solar Model Zones



Typical Experiments

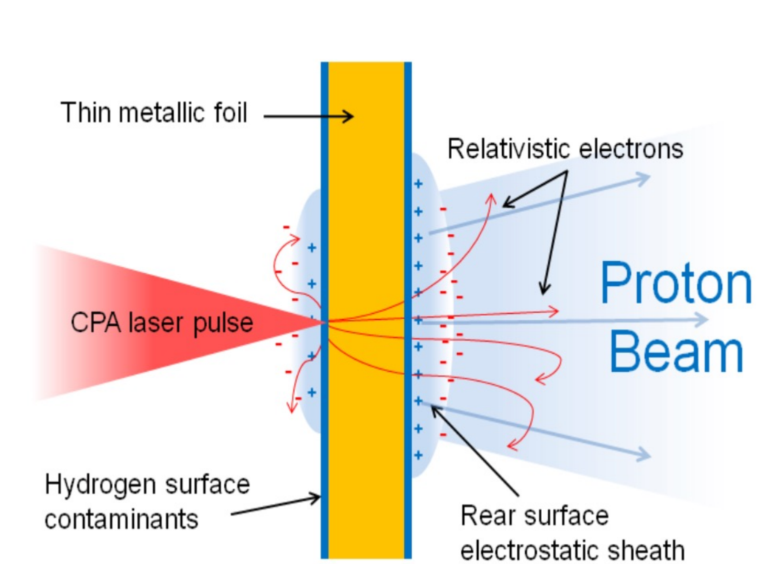


Astro, ICF & HED at T>200 eV, r>0.1 g/cc are limited by under-validated radiative properties models that require rigorous validation

Examples: Sources

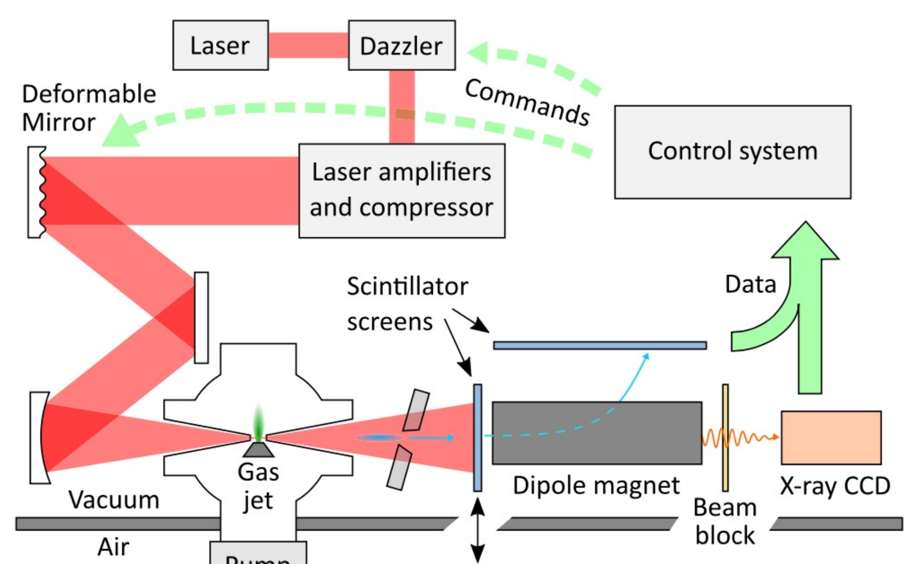
HRR will generate consistent and reproducible secondary source particle/radiation beams for probing/driving experiments

Ion Acceleration



Markey, STFC report (2010)

Wakefield Acceleration



S. Dann, et al., PRAB (2019)

Also: R.J. Shalloo, et al., Nat. Comm. (2021)

High brightness, high flux sources of x-rays, g's, energetic particles (electrons, ions, neutrons, positrons) will enable numerous applications

Examples

Many classes of IFE-relevant experiments will benefit from different features of high-throughput experiments

i. **Laser plasma instabilities**

→ Laser pulse shapes/plasma environments

ii. **dynamic compression physics**

→ probe new phase space

iii. **non-equilibrium physics in warm dense matter**

→ trace evolution of the system in time

iv. **materials EOS and opacity**

→ statistics to minimize error bars

v. **particle and radiation beams****

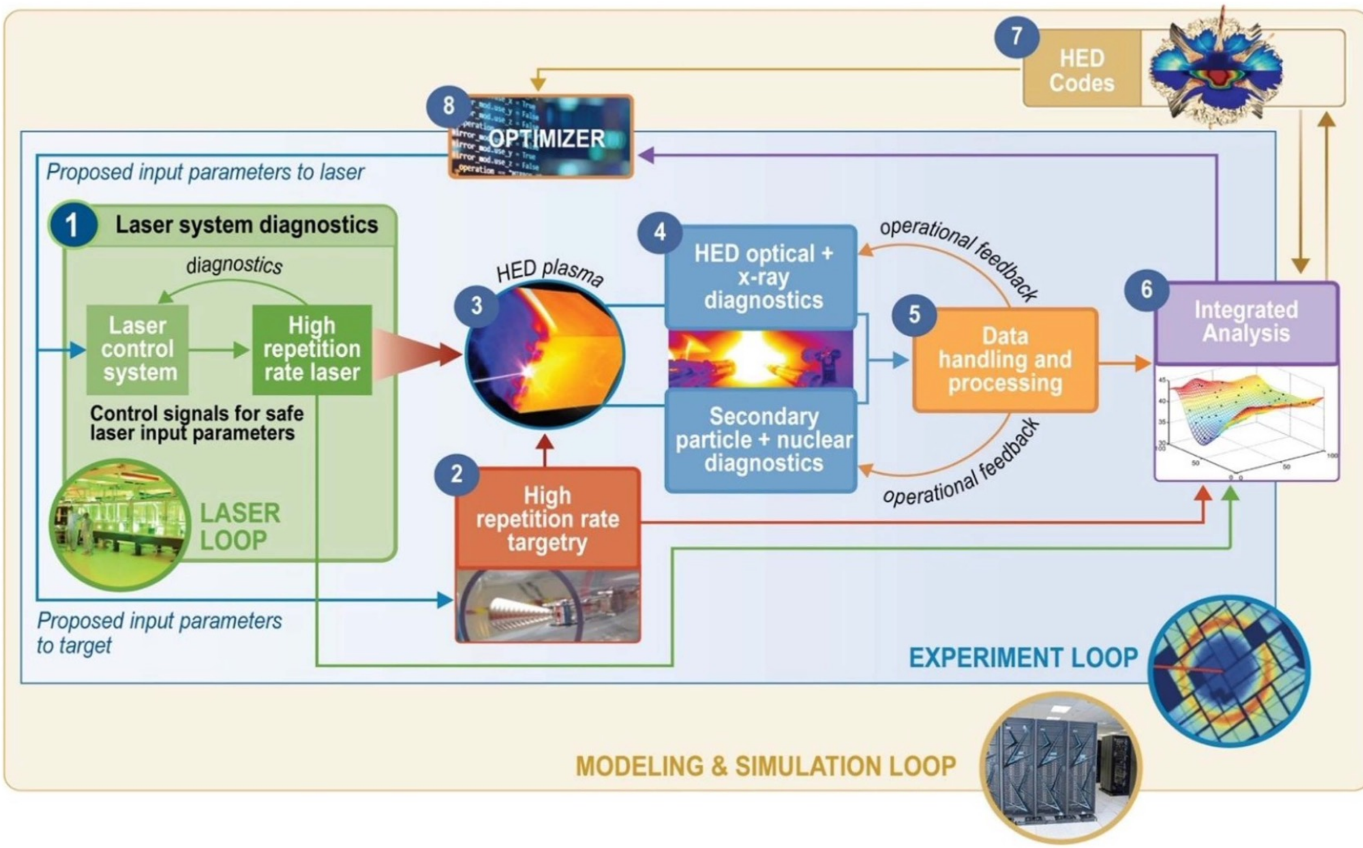
→ consistency, reproducibility, high average brightness

vi. **plasma nuclear physics**

→ high average numbers to probe rare or subtle nuclear rxns**

***See G.J. Williams WP*

HRR is not just driver @ 10 Hz → a fully integrated system that leverages ML and AI in many domains for autonomous operation



T. Ma, et al., "Accelerating the rate of discovery: toward high-repetition-rate HED science". PPCF, (2021)

Challenges that stem from high-rep-rate experiments are starting to be addressed

Machine Learning & Artificial Intelligence are already making large impacts in scientific discovery & fusion

Perspective

The data-driven future of high-energy-density physics

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Article

Magnetic control of tokamak plasmas through deep reinforcement learning

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Open access

Jonas Degrave[1,3], Federico Felici[2,3✉], Jonas Buchli[1,3✉], Michael Neunert[1,3], Brendan Tracey[1,3✉], Francesco Carpanese[1,2,3], Timo Ewalds[1,3], Roland Hafner[1,3], Abbas Abdolmaleki[1], Diego de las Casas[1], Craig Donner[1], Leslie Fritz[1], Cristian Galperti[2], Andrea Huber[1], James Keeling[1], Maria Tsimpoukelli[1], Jackie Kay[1], Antoine Merle[2], Jean-Marc Moret[2], Seb Noury[1], Federico Pesamosca[2], David Pfau[1], Olivier Sauter[2], Cristian Sommariva[2], Stefano Coda[2], Basil Duval[2], Ambrogio Fasoli[2], Pushmeet Kohli[1], Koray Kavukcuoglu[1], Demis Hassabis[1] & Martin Riedmiller[1,3]

Application of machine learning techniques at the CERN Large Hadron Collider

F.F. Van der Veken[*a,b], G. Azzopardi[a,b], F. Blanc[c], L. Coyle[a,c], E. Fol[a,d],

IEEE TRANSACTIONS ON PLASMA SCIENCE, VOL. 48, NO. 1, JANUARY 2020

Transfer Learning to Model Inertial Confinement Fusion Experiments

K. D. Humbird, J. L. Peterson, B. K. Spears, and R. G. McClarren

Automated repair of laser damage on National Ignition Facility optics using machine learning

S. Trummer, G. Larkin, L. Kegelmeyer, M. Nostrand, C. Karkazis, D. Martin, R. Aboud, T. Suratwala
Lawrence Livermore National Laboratory, 7000 East Avenue, Livermore, CA 94550 USA

Deep learning: A guide for practitioners in the physical sciences

Cite as: Phys. Plasmas **25**, 080901 (2018); https://doi.org/10.1063/1.5020791
Submitted: 27 December 2017 . Accepted: 26 June 2018 . Published Online: 15 August 2018

Brian K. Spears, James Brase, Peer-Timo Bremer, Barry Chen, John Field, Jim Gaffney, Michael Kruse, Steve Langer, Katie Lewis, Ryan Nora, Jayson Luc Peterson, Jayaraman Jayaraman Thiagarajan, Brian Van Essen, and Kelli Humbird

Cognitive simulation models for inertial confinement fusion: Combining simulation and experimental data

Cite as: Phys. Plasmas **28**, 042709 (2021); https://doi.org/10.1063/5.0041907
Submitted: 04 January 2021 • Accepted: 26 March 2021 • Published Online: 27 April 2021

K. D. Humbird, J. L. Peterson, J. Salmonson, et al.

ORIGINAL ARTICLE | WILEY

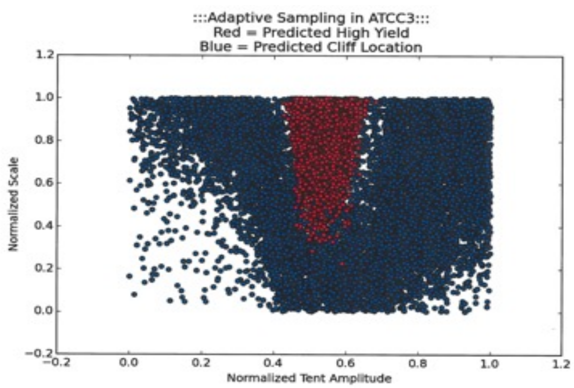
Ensemble simulations of inertial confinement fusion implosions

Ryan Nora | Jayson Luc Peterson | Brian Keith Spears | John Everett Field | Scott Brandon

Examples: ML Apps

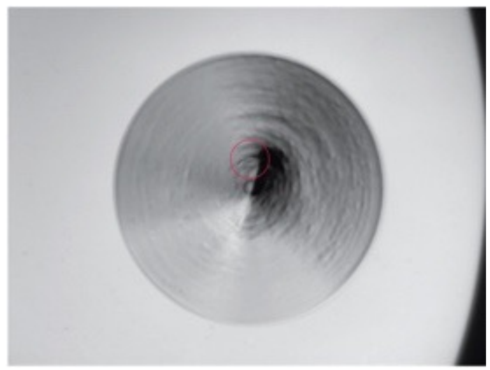
ML can organize & analyze large data sets, help with safe driver operation, and can incorporate experimental data to build real-world-informed models

Regression



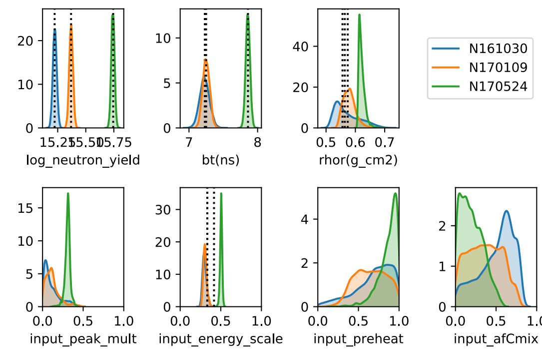
Ensembles/Surrogate models

Classification



NIF Damage Detection

Expt.-informed Models

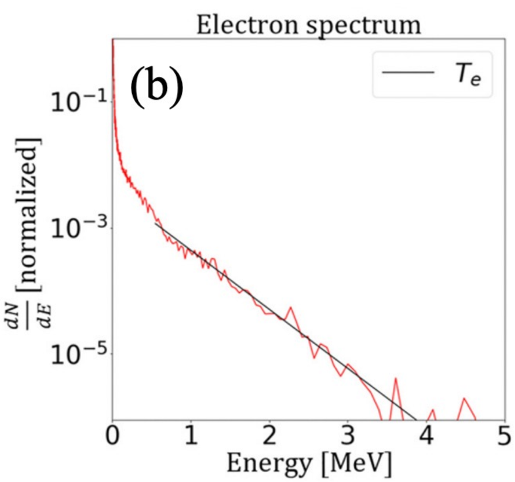


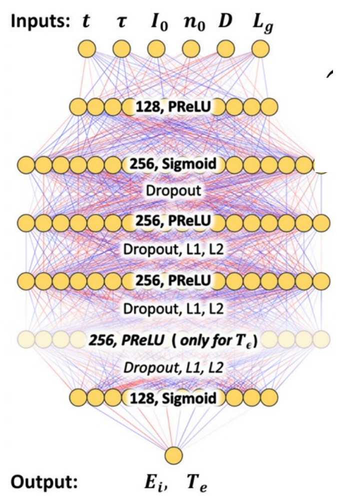
Interpreting experiments

Advances in computational power and ML techniques enable new approaches to data analysis, prediction, and comparing simulations & experiments

ML/AI are being used to explore vast parameter spaces, bridge multi-scale multi-physics multi-fidelity simulations, and optimize designs

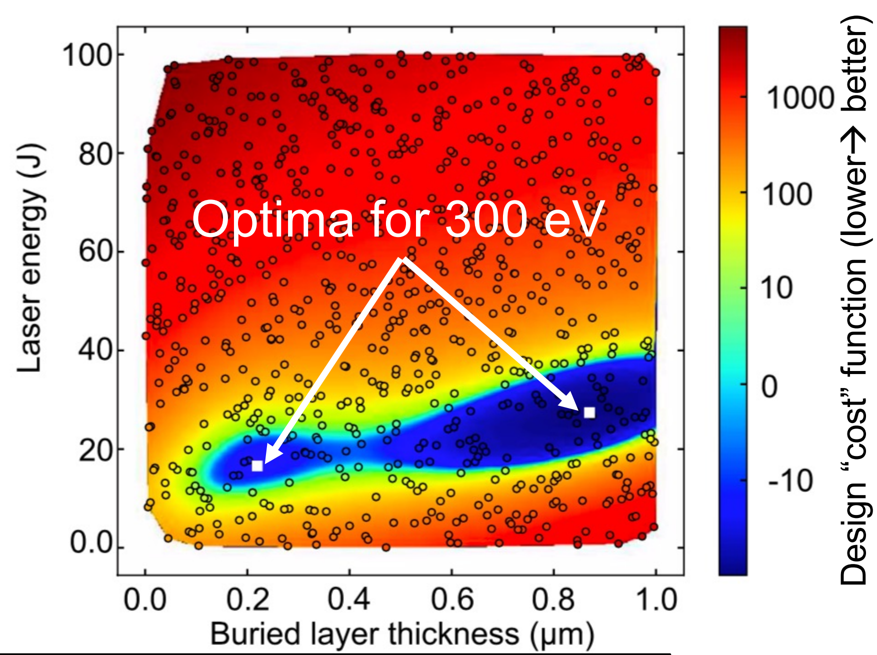
Ensemble PIC Modeling for Particle Source





Djordjević, B. Z., et al. *Physics of Plasmas*, *28*(4), 043105.

Ensemble HYDRA Modeling for Experimental Design

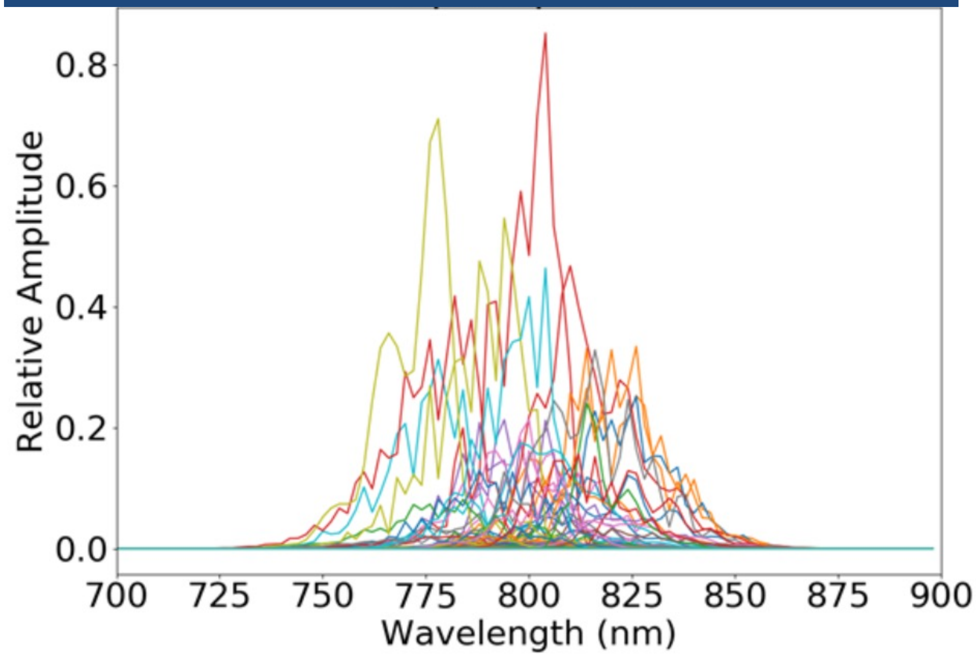


Martin, M. E., London, R. A., et al. High Energy Density Physics, 26, 26-37.

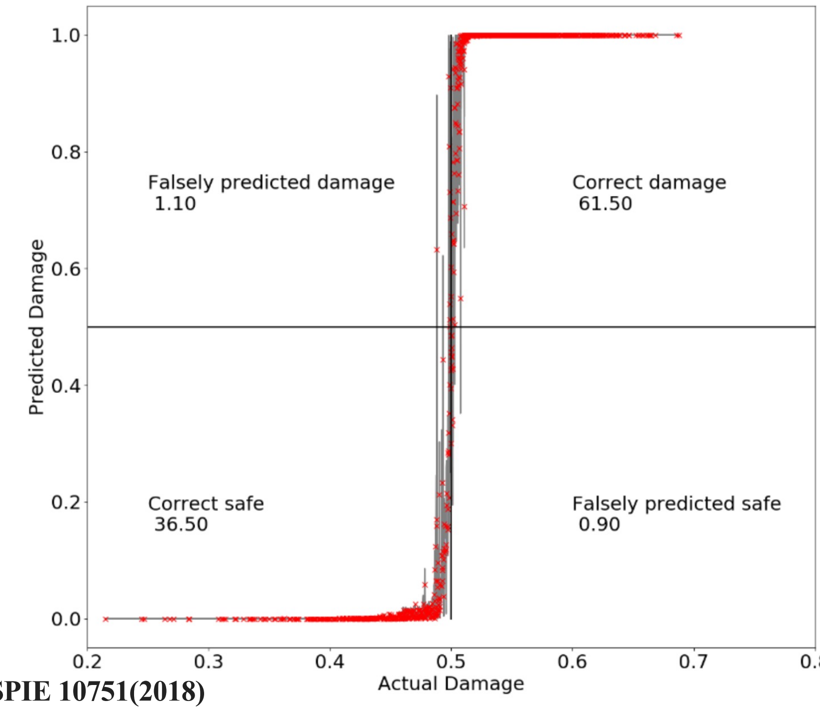
Simulations have a significant head start on leveraging ML → blueprints for experiments at HRR

ML in tandem with accurate models can be trained to ensure safe and accurate driver operation

Laser Input Spectra



NN-predicted Laser Damage



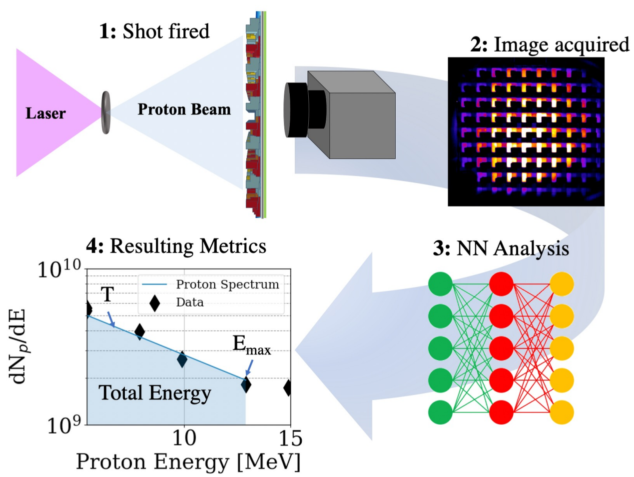
T. Galvin, et al., Proc. of SPIE 10751(2018)

Crucial in science experiments and for IFE → cannot afford downtime

ML Examples: Diagnostics

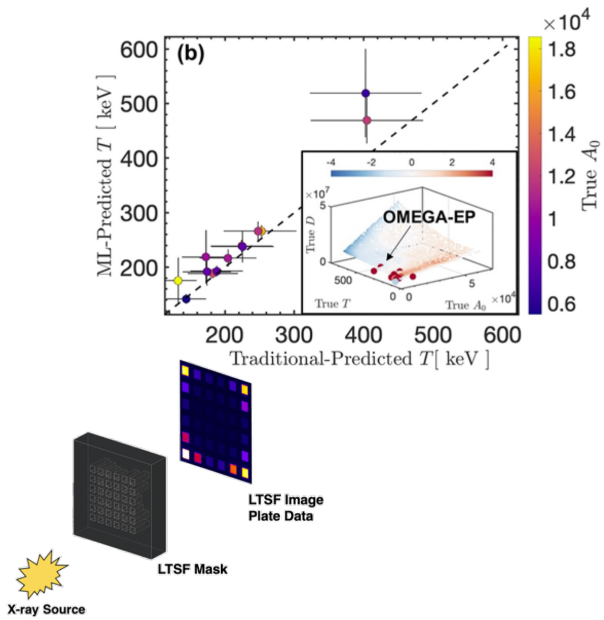
Diagnostics must be HRR-capable while remaining robust to extremely hostile experimental environments (EMP, neutrons, etc.)

Proton Beams



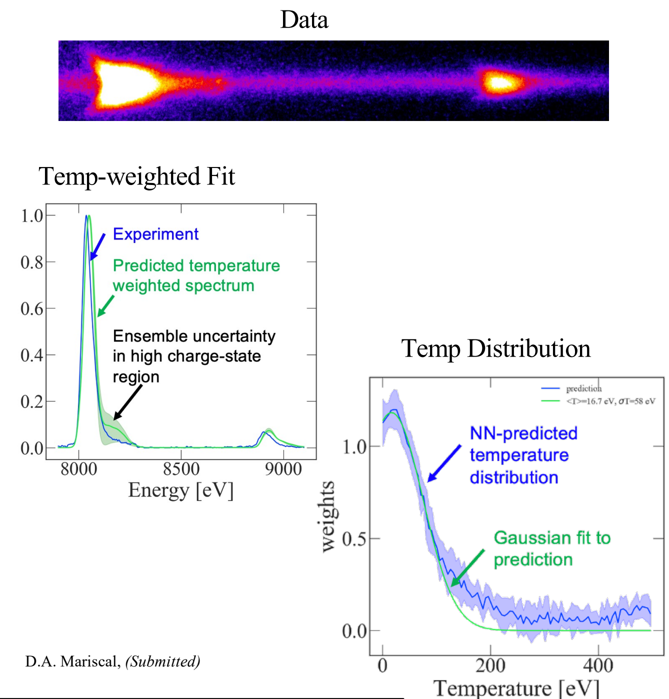
D.A. Mariscal, *et al*, "Design of Flexible Proton Beam Imaging Energy Spectrometers (PROBIES)", *PPCF* (2021)

Multi-keV X-rays



R.A. Simpson, et al., "Development of a deep learning based automated data analysis for step-filter x-ray spectrometers in support of high-repetition rate short-pulse laser-driven acceleration experiments", RSI 92, 075101 (2021)

X-ray Spectra



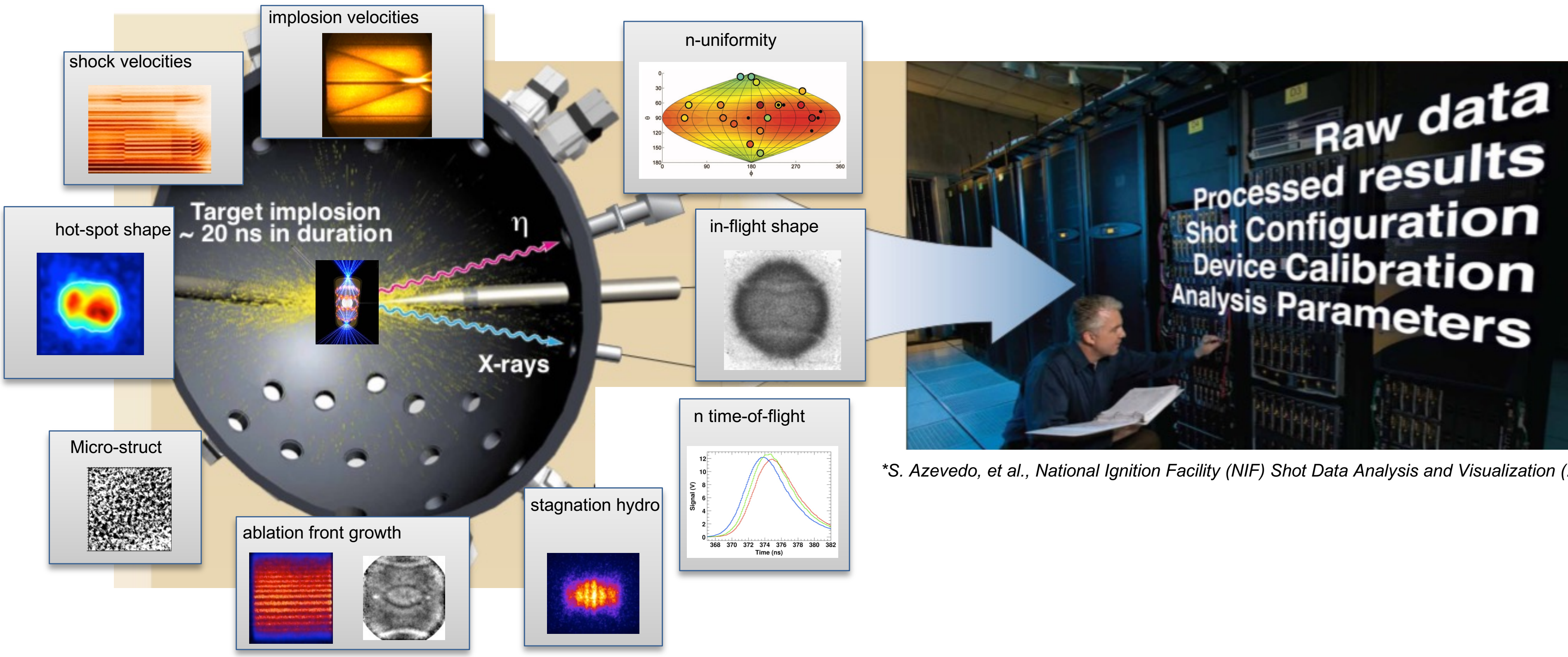
D.A. Mariscal, *(Submitted)*

Incorporating ML into diagnostics (edge) will be necessary for rapid and accurate analysis that leaves time for on-the-fly decisions**

**See G.G. Scott WP

Data Handling

ML can help processing/storing data gathered from high rep-rate experiments

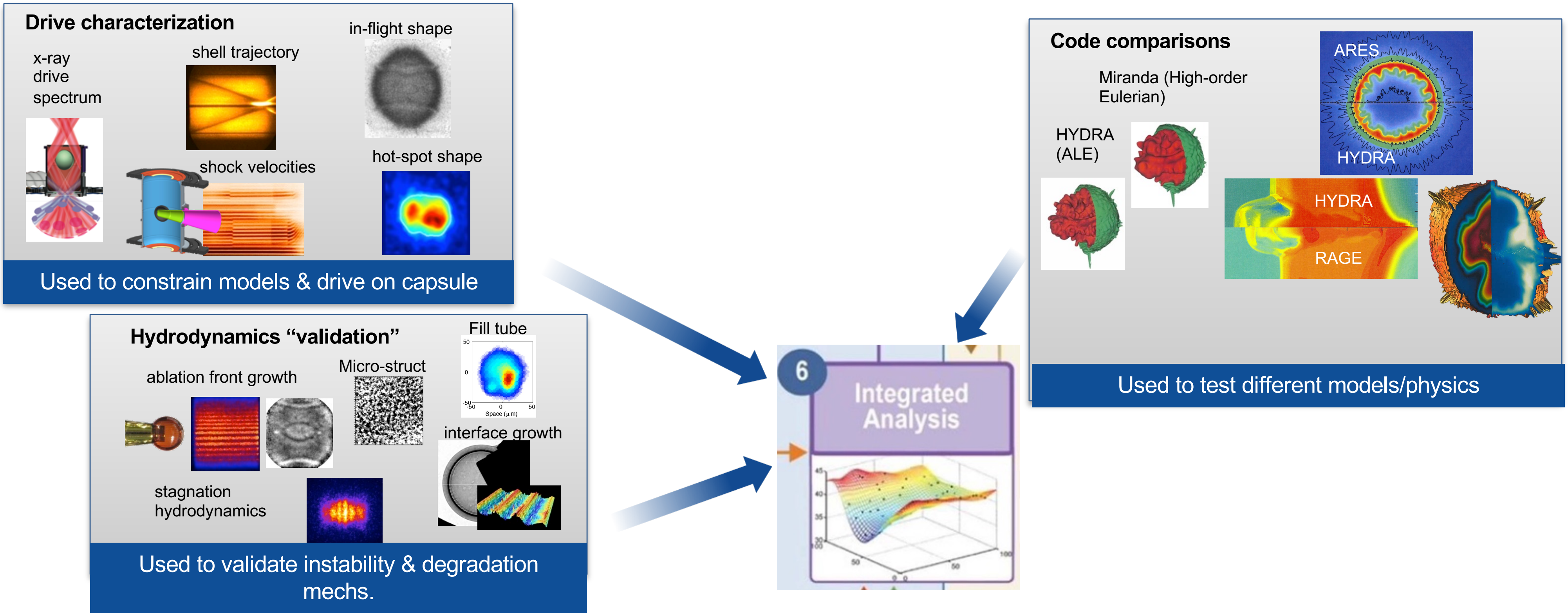


S. Azevedo, et al., National Ignition Facility (NIF) Shot Data Analysis and Visualization (2012)

Leverage knowledge from low shot-rate facilities (lasers, pulsed-power) and high rep-rate facilities (accelerators) to handle data streams

Data Handling

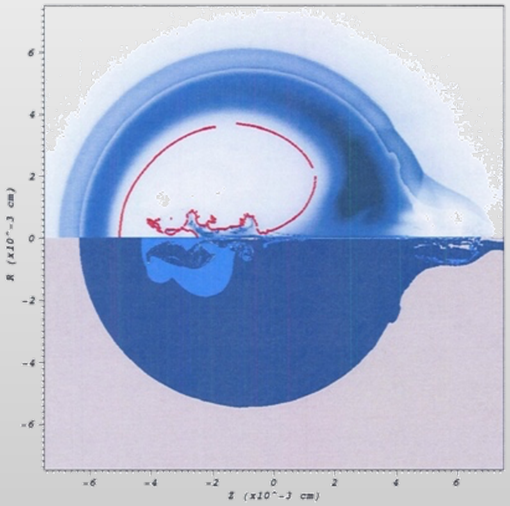
Heterogenous data is used to benchmark HED codes → design the next generation of experiments (currently over weeks/months/years)



Reduced data representations will be necessary for experiments and simulations to "communicate"

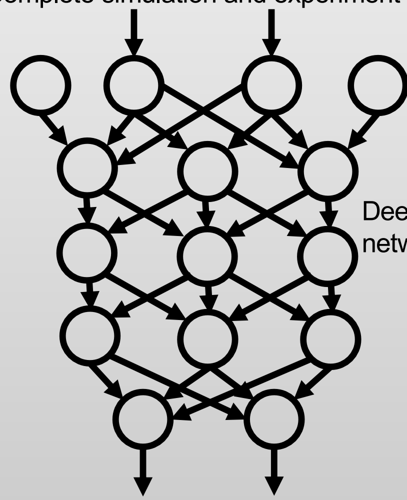
Machine learning allows us to improve predictive modeling across applications

High-performance computing

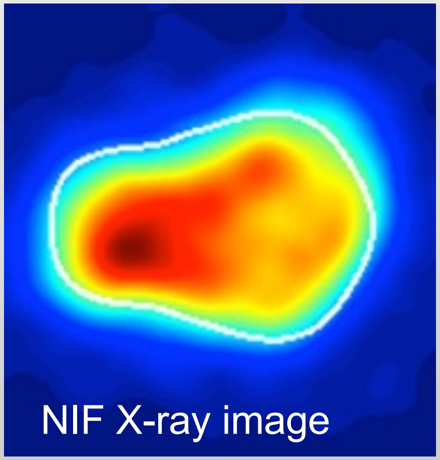


HYDRA simulation

Machine learning to compare simulation and experiment



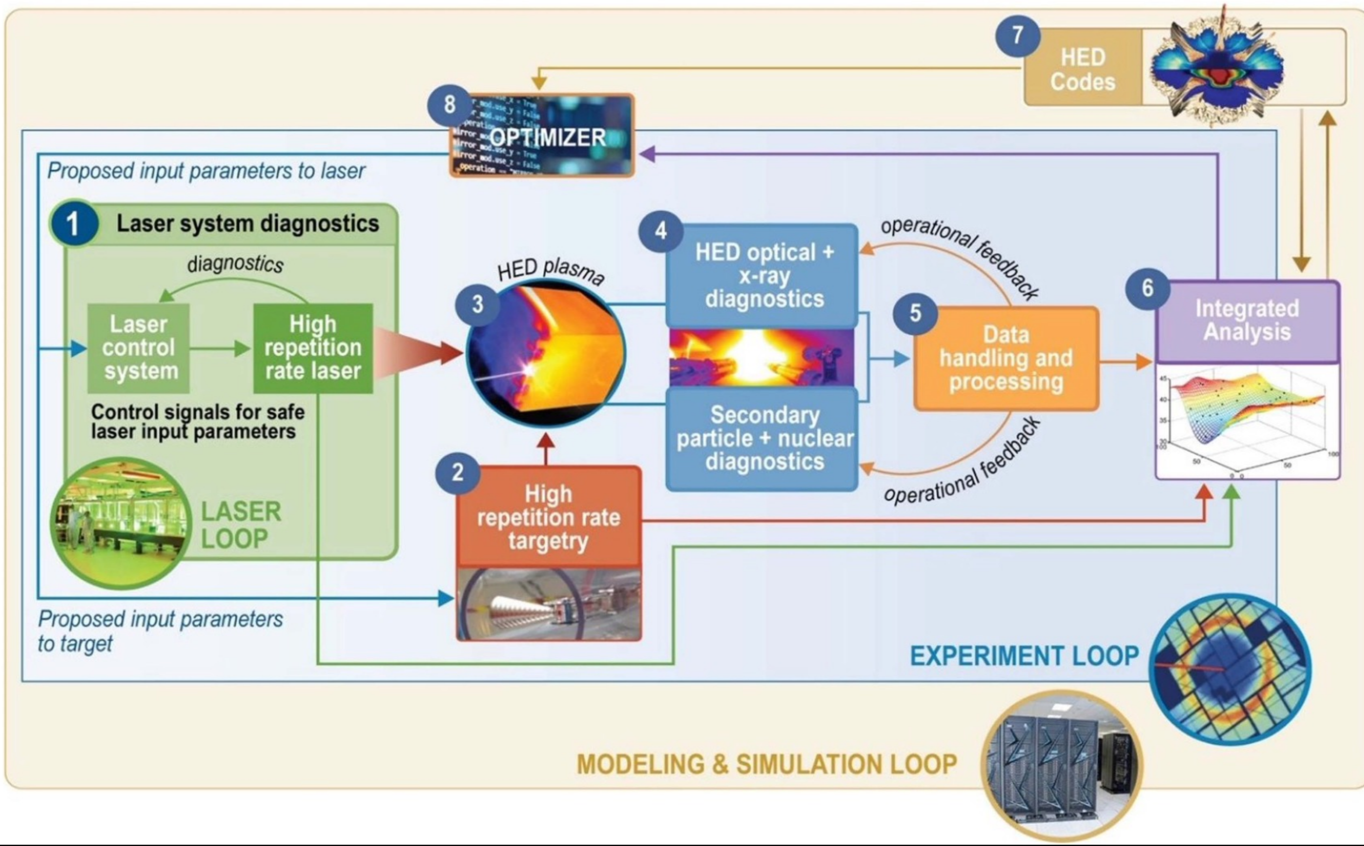
Large-scale experiments



Machine learning will allow us to use our full data sets to make our models more predictive

Recent demos: Humbird, et al., IEEE TRANS PLAS SCI 48, (2020), Gopalaswamy, Varchas, et al. Nature 565.7741 (2019)

Most of the enabling technology has been demonstrated → must be integrated



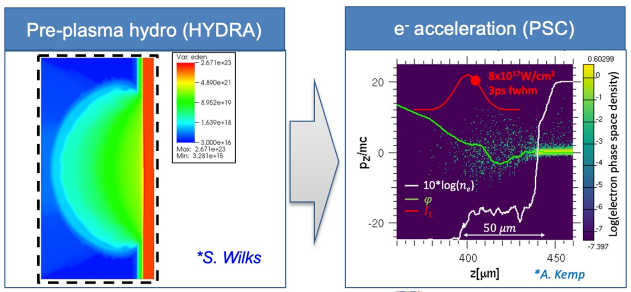
T. Ma, et al., "Accelerating the rate of discovery: toward high-repetition-rate HED science". PPCF, (2021)

ML & AI will be crucial to increasing the rate while maintaining high fidelity

To increase the rate of learning from HRR facilities in support of IFE, experiments and simulations must be integrated through ML and AI

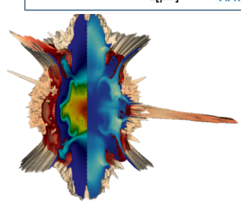
Simulations

Multi-physics, multi-scale

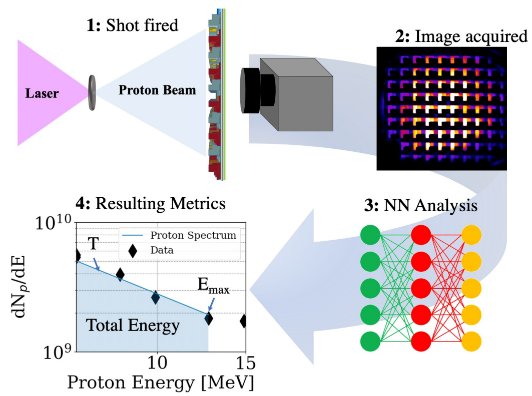


Multi-fidelity

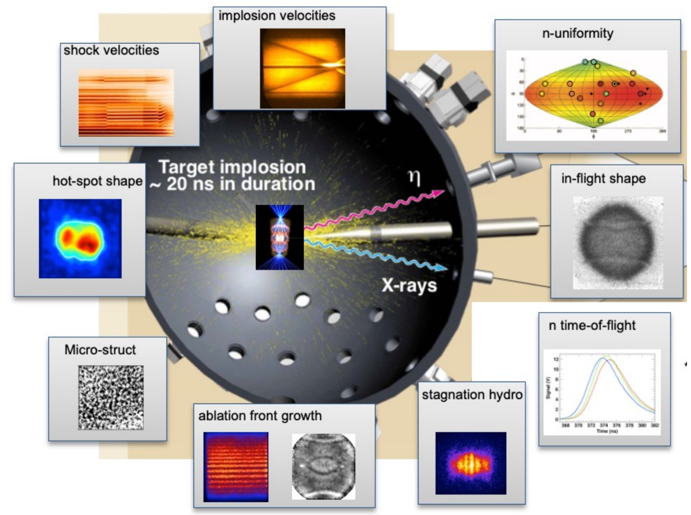
- Low = 1,000's
- High = 10's



Experiments



Data Handling



- Connect multi-physics, multi-scale, multi-fidelity models
- Rapid, accurate, heterogeneous data analysis → compared to simulation models
- Pipelines/filtration/storage

Tech should be deployed & tested on existing facilities/capabilities to build up to full IFE → will contribute to HED, ICF, NNSA missions, LaserNetUS, etc. along the way

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